

## Postprint: Downscaling GPM Satellite Precipitation Data in the Yellow River Basin Using the MGWR Model

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**Date:** 2023-08-01T00:00:00+00:00

### Abstract

The Yellow River Basin encompasses a vast territory, yet meteorological stations are sparsely distributed, leading to a scarcity of meteorological data. Satellite-based precipitation measurements can serve as a crucial supplement to meteorological station observations; however, their limited spatial resolution constrains their effectiveness in regional studies. This study takes the Yellow River Basin as the research area and focuses on the Global Precipitation Measurement (GPM) satellite precipitation product. Using precipitation data from 2002, 2012, and 2020 as three representative climatic years—dry, normal, and wet years, respectively—and comprehensively considering multiple influencing factors that reflect the spatial distribution characteristics of precipitation—including Normalized Difference Vegetation Index (NDVI), Digital Elevation Model (DEM), slope, Land Surface Temperature (LST), and wind speed (WDS)—along with their spatial non-stationarity features, two downscaling methods—the Geographically Weighted Regression (GWR) model and the Mixed Geographically Weighted Regression (MGWR) model—were employed to derive downscaled precipitation data at 1 km spatial resolution for the Yellow River Basin. The downscaling results were subsequently validated using ground-based meteorological station data. The findings demonstrate that: (1) GPM annual precipitation data exhibits high correlation with ground meteorological station observations in the Yellow River Basin for the years 2002, 2012, and 2020. (2) The precipitation data downscaled using the MGWR model achieves significantly enhanced spatial resolution and provides superior representation of spatial details in precipitation variation compared to the GWR model. (3) Across the three typical climatic years, the MGWR model demonstrates higher accuracy relative to the GWR model specifically during the normal precipitation year. The research outcomes can furnish macro-level reference and guidance for precipitation downscaling studies in relevant regional contexts, thereby advancing regional climate and hydrological research.

## Full Text

### Abstract

The Yellow River Basin is vast, but meteorological stations are sparsely distributed, leading to a shortage of meteorological data. Satellite precipitation can serve as an important supplement to meteorological station observations, but its limited spatial resolution restricts its utility in regional studies. Taking the Yellow River Basin as the study area and targeting the Global Precipitation Measurement (GPM) satellite precipitation product, this study uses precipitation data from 2002, 2012, and 2020 as three typical climate years representing dry, standard, and wet years. Based on comprehensive consideration of multiple factors reflecting the spatial distribution characteristics of precipitation—including Normalized Difference Vegetation Index (NDVI), Digital Elevation Model (DEM), slope, Land Surface Temperature (LST), and wind speed (WDS)—and their spatial non-stationarity characteristics, two downscaling methods (Geographically Weighted Regression (GWR) model and Mixed Geographically Weighted Regression (MGWR) model) were employed to obtain 1-km spatial resolution downscaled precipitation data for the Yellow River Basin. The downscaling results were further validated using ground meteorological station data. The results show that: (1) GPM data exhibits high correlation with ground meteorological station observations in the Yellow River Basin across the three typical climate years. (2) The MGWR model significantly improved the spatial resolution of precipitation data and demonstrated superior performance in expressing spatial details of precipitation variation compared to the GWR model. (3) The MGWR model achieved higher accuracy than the GWR model in the precipitation standard year. The research results can provide macro-level reference and guidance for precipitation downscaling studies in related regions, promoting regional climate and hydrological research.

**Keywords:** Mixed Geographically Weighted Regression model (MGWR); Geographically Weighted Regression model (GWR); Global Precipitation Measurement (GPM); Yellow River Basin

## 1. Introduction

Precipitation is one of the key elements in the global water cycle, and obtaining high spatiotemporal resolution precipitation data is of great significance for ecology, hydrology, and meteorology research [1]. Traditional precipitation observation methods mainly include rain gauges and radar. However, the limited number of such observation stations and their uneven spatial distribution result in a scarcity of high spatial resolution precipitation data, which constrains precipitation research [2]. Meanwhile, precipitation exhibits high spatiotemporal heterogeneity [3], making it difficult for traditional observation methods to accurately reflect its distribution patterns. With the development of satellite technology, remote sensing retrieval of precipitation provides a new approach for obtaining precipitation data. Satellite remote sensing data are unaffected

by weather and complex terrain, provide complete land and ocean coverage, enable large-area observations, and operate under all-weather conditions. Consequently, satellite data have become an important source of information for obtaining spatiotemporal precipitation variation data.

In recent decades, many institutions and government organizations have developed a series of regional and global precipitation datasets. For example, artificial neural networks have been used to estimate precipitation from remote sensing satellite products [4]; the Global Precipitation Climatology Project (GPCP) [5]; the Tropical Rainfall Measuring Mission (TRMM) [6]; and the Global Precipitation Measurement (GPM) program [7] provide powerful data support for related research. The GPM satellite program is a satellite monitoring system for meteorological forecasting jointly constructed by NASA, the Japan Aerospace Exploration Agency (JAXA), and other international organizations such as the European Union.

Since its release, the GPM IMERG (Integrated Multi-satellite Retrievals for GPM) precipitation product has been widely applied in numerous studies worldwide. Anjum et al. [8] conducted a four-season accuracy assessment of GPM data in northern Pakistan and concluded that GPM data provide more reliable precipitation estimates. Tan and Duan [9] compared GPM and TRMM precipitation data in Singapore, demonstrating that GPM data exhibit better performance in representing precipitation spatial variability and estimation capability. Arshad et al. [10] found that GPM data can more accurately estimate precipitation in China, with significantly improved accuracy in Xinjiang and the Tibetan Plateau regions. According to existing research, the performance of GPM data varies considerably across different regions, time scales, and terrain conditions.

Compared with TRMM, GPM data have improved spatial resolution, observation accuracy, and accuracy [7], providing more reliable precipitation estimates. However, their spatial resolution is often too coarse to present subtle changes in precipitation spatial distribution, making it necessary to downscale satellite precipitation data products to improve their precision and spatial resolution [11] for refined hydrological analysis at regional or smaller scales.

Downscaling methods can be broadly divided into two categories: dynamic downscaling and statistical downscaling [12]. Compared with dynamic downscaling, statistical downscaling is widely used in satellite remote sensing precipitation product downscaling research due to its advantages of smaller computational requirements, time savings, diverse and flexible methods, and easier operation. The Geographically Weighted Regression (GWR) model is a representative statistical downscaling method that has been widely applied in satellite precipitation data product downscaling research. Immerzeel et al. [13] established a GWR model between TRMM precipitation data and NDVI to obtain annual precipitation data at 1 km spatial resolution for the Iberian Peninsula. Jia et al. [14] built upon this work by constructing a multiple linear regression model between TRMM data and NDVI, DEM, and LST to improve the

spatial resolution of TRMM precipitation data to 1 km in the Qaidam Basin. Wen et al. [15] used the GWR model to downscale GPM precipitation data in Shaanxi Province and found that the downscaled precipitation data had good accuracy and could accurately reflect precipitation distribution within Shaanxi. Zeng et al. [16] conducted TRMM precipitation data downscaling research in the Qinling-Bashan mountainous area using the GWR model and found that the GWR model has strong applicability for TRMM precipitation data. Cui et al. [17] used the GWR model to downscale TRMM and GPM precipitation data in China's three major river basins and obtained 1 km resolution downscaled precipitation data for the three basins.

The GWR model is suitable for modeling when environmental variables have obvious spatial non-stationarity. However, in many practical problems, environmental variables include both global variables and local variables, and some environmental variables may not exhibit spatial non-stationarity or have negligible spatial non-stationarity. Precipitation is a complex natural phenomenon characterized by significant variability in both time and space [18], and factors affecting precipitation may simultaneously include both spatially stationary and spatially non-stationary types. In the study by Arshad et al. [10], both GWR and MGWR models were established between GPM precipitation data and NDVI, LST, and wind speed (WDS), and through Geographical Ratio Analysis (GRA) and Geographical Difference Analysis (GDA), it was found that compared with GPM data, the detection capability for weak precipitation ( $<0.5 \text{ mm} \cdot \text{h}^{-1}$ ) and solid precipitation was improved. By merging downscaled precipitation data with rain gauge station precipitation data, the accuracy of downscaled precipitation data was further improved. Therefore, this paper uses the MGWR model to evaluate the downscaling effect of satellite precipitation products, which can provide macro-level reference and guidance for precipitation downscaling research in related regions and promote regional climate and hydrological research.

## 2. Study Area and Data

### 2.1 Study Area Overview

This study takes the Yellow River Basin ( $95^{\circ}50' - 119^{\circ}06' \text{ E}$ ,  $32^{\circ}06' - 41^{\circ}48' \text{ N}$ ) as the research area. The Yellow River originates from the Bayan Har Mountains and flows sequentially through the Tibetan Plateau, Inner Mongolia Plateau, Loess Plateau, and the downstream alluvial plain, crossing China's three topographic steps (Fig. 1). The Yellow River Basin belongs to typical arid, semi-arid, and semi-humid climate zones in China, with a total basin area of approximately  $79.46 \times 10^4 \text{ km}^2$ . According to the classification scheme provided by the Yellow River Conservancy Commission, the Yellow River Basin is divided into upper, middle, and lower reaches.

The Yellow River Basin is vast, with overall terrain that is high in the west and low in the east, featuring significant undulation and complex landforms. From

west to east, it is divided into western, central, and eastern regions, dominated by the Tibetan Plateau region, Loess Plateau region, and Huang-Huai-Hai Plain region, respectively. Due to the complex influence of atmospheric circulation and monsoon circulation, the basin exhibits significant east-west climate differences and uneven spatial distribution of precipitation [19]. However, the basin has strong evaporation capacity, resulting in drought events with wide impact areas, long duration, and high frequency [20]. Therefore, obtaining accurate and rapid precipitation data is crucial for drought monitoring in the Yellow River Basin.

[Figure 1: see original paper]

## 2.2 Data Sources

**2.2.1 Precipitation Data** The GPM satellite precipitation data (IMERG\_{V06} data) used in this study were obtained from <https://www.nasa.gov/>. The GPM satellite program produces multiple levels of products based on different data retrieval algorithms. This study selected the IMERG\_{Final} product, which was released in March 2021. It integrates information obtained from passive microwave and infrared sensors, performs mutual calibration, merging, interpolation, and fusion to generate consistent precipitation data, enabling precipitation estimation from June 2000 to the present [21]. The spatial resolution is  $0.1^\circ \times 0.1^\circ$ , and the temporal resolution is 1 day.

**2.2.2 Environmental Variables** The NDVI data were obtained from MOD13A3 monthly composite vegetation index data (<https://ladsweb.modaps.eosdis.nasa.gov/>) with a spatial resolution of 1 km. The LST data were obtained from MOD11A2 data products in the MODIS LST series. DEM data were obtained from the SRTM DEM dataset on the Geospatial Data Cloud (<https://www.gscloud.cn/>) with a spatial resolution of 90 m, from which slope (Slope) was further derived using ArcGIS software.

**2.2.3 Station Data** Meteorological station observation data were obtained from the National Meteorological Information Center (<http://data.cma.cn>). This study selected precipitation data from 71 meteorological stations in the Yellow River Basin and GPM data. The station data were interpolated to obtain  $0.1^\circ \times 0.1^\circ$  resolution data. GPM data were used to extract annual cumulative precipitation information for the Yellow River Basin from 2001 to 2020, and the annual average precipitation was calculated. By comparing the annual average precipitation, three typical climate years were selected (2002 with the lowest precipitation value as the dry year, 2012 with the value closest to the multi-year average as the standard year, and 2020 with the highest precipitation value as the wet year) to conduct research on the downscaling accuracy of GPM data under different downscaling models in the Yellow River Basin (Fig. 2).

[Figure 2: see original paper]

### 3. Methods

#### 3.1 Downscaling Methods

The GWR model, proposed by Brunson et al. [22], is a local regression analysis method used to detect spatial non-stationarity and an extension of traditional linear regression models. The basic concept is that the relationship between variables changes with spatial location. By introducing spatial relationship weights in regression, parameters in the global model are set as functions of geographic location to estimate the variation of parameters between relevant variables and explanatory variables at any location in the study area. Previous studies have shown that NDVI, DEM, LST, slope, and wind speed are important factors affecting precipitation. Therefore, this study uses these five environmental variables as auxiliary factors, precipitation data as the true value, and performs accuracy verification on GPM satellite precipitation products before downscaling.

The basic formula of the GWR model is:

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^n \beta_k(u_i, v_i) X_{ik} + \varepsilon_i$$

where  $Y_i$  is the precipitation at point  $i$  (mm);  $(u_i, v_i)$  are the longitude and latitude coordinates of point  $i$ ;  $\beta_0(u_i, v_i)$  is the constant term;  $\beta_k(u_i, v_i)$  is the  $k$ th regression parameter at location  $i$ ;  $X_{ik}$  is the value of the  $k$ th spatial factor at location  $i$ ; and  $\varepsilon_i$  is the residual at each location.

The MGWR model was proposed by Brunson et al. [23] based on the GWR model. In practical problems, spatial relationships include explanatory variables that have global effects on the dependent variable and those that have local effects. Therefore, complete spatial modeling of a geographic problem requires distinguishing between global and local variables in the model. Precipitation has obvious spatial heterogeneity, and factors affecting precipitation may simultaneously include both spatially stationary and non-stationary types. The MGWR model is an effective data analysis method that can address spatial non-stationarity problems by introducing global variables.

The MGWR model formula is:

$$Y_i = \sum_{j=1}^m \alpha_j X_{ij} + \sum_{l=1}^n \beta_l(u_i, v_i) X_{il} + \varepsilon_i$$

where  $X_{ij}$  and  $X_{il}$  are the values of the  $j$ th and  $l$ th spatial factors at location  $i$ , respectively;  $\alpha_j$  is the regression parameter for global regression;  $\beta_l(u_i, v_i)$  is the regression parameter for local regression;  $j = 1, 2, \dots, m$ ; and  $l = 1, 2, \dots, n$ .

In this study, geographic variability testing was used to calculate difference standard values. When the difference standard value is less than 0.5, the auxiliary variable has weak spatial variability and is treated as a global variable; otherwise, it is treated as a local variable (Table 1).

### 3.2 Downscaling Process

The downscaling method is based on two fundamental assumptions [24]: First, a spatial relationship exists between precipitation and environmental variables that can be simulated and processed using regression models. Second, models established at low spatial resolution can be used for high spatial resolution precipitation prediction using environmental variable data. This study performs downscaling operations on GPM data, and the flowchart in Fig. 3 summarizes the MGWR model downscaling process. The specific steps are as follows:

- 1) Environmental variable data and original GPM data were resampled to the same spatial resolution using the Kriging interpolation method for matching.
- 2) Global and local variables among the environmental variables were screened through geographic variability testing, and the relationship between resampled environmental variables and GPM data was established.
- 3) The resampled environmental variable data and original GPM data were used to build the GWR model, obtaining the constant term, corresponding coefficients for environmental variables, and residual results. According to the division of global and local variables, the resampled global and local variables were used to build the MGWR model following Equation (2), obtaining the MGWR model constant term, corresponding coefficients for environmental variables, and residual results.
- 4) The constant term, coefficient term, and residual data from the GWR and MGWR models at  $0.1^{\circ} \times 0.1^{\circ}$  spatial resolution were rasterized and resampled to  $1 \text{ km} \times 1 \text{ km}$  using the Kriging interpolation method.
- 5) According to Equation (1) and Equation (2),  $1 \text{ km} \times 1 \text{ km}$  resolution predicted precipitation data after GWR and MGWR model downscaling were calculated, respectively.

[Figure 3: see original paper]

[Figure 4: see original paper]

### 3.3 Evaluation Metrics

To verify the accuracy of downscaling results, ground meteorological station measurements were used as true values for comparison and validation with downscaling results. Three metrics were adopted: coefficient of determination ( $R^2$ ), bias (Bias), and root mean square error (RMSE).  $R^2$ , also known as goodness-of-fit, reveals the correlation between downscaling results and true values, with

higher values indicating stronger correlation. Bias represents the deviation between downscaling results and true precipitation values, with smaller values indicating closer agreement. RMSE represents the degree of deviation between downscaling results and true values, with smaller values indicating better performance. The calculation formulas are as follows:

$$\text{Bias} = \frac{\sum_{i=1}^n (X_i - Y_i)}{\sum_{i=1}^n Y_i} \times 100\%$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (X_i - Y_i)^2}{n}}$$

where  $X_i$  and  $\bar{X}$  are the downscaled GPM grid values and their mean, respectively;  $Y_i$  and  $\bar{Y}$  are the meteorological station data and their mean, respectively; and  $n$  is the number of meteorological stations.

## 4. Results

### 4.1 Original Data Accuracy Verification

The spatial distribution of GPM data precipitation in the Yellow River Basin is shown in Fig. 5. Using precipitation data from 71 ground meteorological observation stations as true values, validation was performed (Fig. 5). In the three typical climate years of the Yellow River Basin, the  $R^2$  values of GPM data were all greater than 0.5, indicating good correlation between GPM data and true values. However, due to the nonlinear characteristics of precipitation, limitations in spaceborne radar detection performance, and retrieval technology, there are certain differences between GPM data and actual precipitation.

[Figure 5: see original paper]

### 4.2 Downscaling Results and Analysis

#### 4.2.1 GWR Model Downscaling Results and Accuracy Analysis

The GWR model was used to downscale GPM data, obtaining 1 km  $\times$  1 km spatial resolution predicted annual precipitation data spatial distribution in the three typical climate years. The spatial distribution of precipitation remains consistent with GPM data overall, and as spatial resolution increases, precipitation spatial distribution details become clearer compared with GPM data.

Quantitative accuracy analysis of GWR data (Fig. 6) shows that in the three typical climate years, the correlation of GWR data slightly decreased compared with GPM data. In the dry year (2002), the decrease was most obvious, with  $R^2$  decreasing by 0.11. In the standard year (2012),  $R^2$  decreased by 0.05, while in the wet year (2020),  $R^2$  decreased by only 0.02. Overall, the GWR model performed better in the precipitation standard year. The Bias and RMSE of

the three typical climate years both slightly increased. In general, the GWR model performed well in the precipitation standard year.

[Figure 6: see original paper]

#### 4.2.2 MGWR Model Downscaling Results and Accuracy Analysis

The MGWR model was used to downscale GPM data, obtaining 1 km $\times$ 1 km spatial resolution predicted annual precipitation data spatial distribution in the Yellow River Basin (Fig. 7). The figure shows that MGWR downscaled data (hereafter MGWR data) demonstrate significant improvement in precipitation spatial distribution details compared with GWR data. The precipitation spatial distribution trend remains consistent with GPM data, but with stronger expression capability and smoother edges.

Quantitative accuracy analysis of MGWR data (Fig. 7) shows that in the three typical climate years, the  $R^2$  values of MGWR data are all between 0.5 and 0.8. The standard year (2012) had the highest  $R^2$ , while the dry year (2002) and wet year (2020) had relatively lower  $R^2$  values. As GPM data  $R^2$  increased, MGWR data  $R^2$  also increased to some extent, indicating that the MGWR model performed better in the precipitation wet year. The accuracy of downscaled data has certain dependence on the original data.

[Figure 7: see original paper]

#### 4.3 Comparison of Two Model Downscaling Results

The spatial resolution of both downscaled datasets improved from 0.1 $^{\circ}$  $\times$ 0.1 $^{\circ}$  to 1 km $\times$ 1 km. The peak precipitation area is mainly located in the southern part of the Yellow River Basin. In the standard year (2012) and wet year (2020), there is another precipitation peak area in the eastern part of the Yellow River Basin, which is consistent with the GPM data. To some extent, this can more clearly reflect the spatial distribution pattern of precipitation in the Yellow River Basin.

Compared with the GWR model, the MGWR model has stronger spatial detail expression capability, with smoother precipitation data spatial distribution edges. In the three typical climate years, the MGWR model can better express precipitation spatial distribution details in areas with abundant precipitation. The spatial distribution trend of annual precipitation in the three typical climate years is roughly increasing from north to south. Similar to GPM data, the correlation of precipitation results within the Yellow River Basin is slightly lower than GPM data. The difference is that in areas with abundant precipitation, MGWR data can better express the detail effect of precipitation spatial distribution.

In the three typical climate years, the  $R^2$  values of MGWR data are all lower than those of GPM data. In the dry year (2002), the  $R^2$  reduction was most obvious, decreasing by 0.12 compared with GPM data. In the wet year (2020),

the  $R^2$  of MGWR data slightly increased compared with GPM data, rising from 0.65 to 0.66. The Bias and RMSE of the three typical climate years both slightly increased, but in the wet year (2020), the Bias decreased. Overall, MGWR data can better restore GPM precipitation observation information in the Yellow River Basin region and performs better in areas with abundant precipitation.

The spatial distribution of downscaling differences in the Yellow River Basin (Fig. 8) shows that in the dry year (2002) and standard year (2012), precipitation differences are mostly positive, with a wide distribution range of positive values. In the wet year (2020), the southern part of the Yellow River Basin shows positive differences, while the northern part has relatively more negative values. Overall, the amount of precipitation affects the value range of GPM data differences, leading to changes in the value range of downscaling results. The total precipitation in the dry year (2002) and standard year (2012) is relatively smaller, so the value range of their differences is also relatively smaller. The total precipitation in the wet year (2020) is relatively larger, so the value range of its differences is also relatively larger.

[Figure 8: see original paper]

## 5. Discussion

The GWR model downscaling method has been widely applied by many scholars in downscaling research of satellite remote sensing precipitation products [25]. However, its use is limited by whether environmental variables have spatial stationarity. Precipitation is a complex natural phenomenon characterized by significant variability in both time and space [18], and factors affecting precipitation may simultaneously include both spatially stationary and non-stationary types. Therefore, analyzing the downscaling effect of the MGWR model on GPM data in the Yellow River Basin under different dry and wet climate conditions can provide macro-level reference and guidance for precipitation downscaling research in related regions and promote regional climate and hydrological research.

Overall, this study confirms the advantages of the MGWR model over the traditional GWR model in precipitation data downscaling. Based on the MGWR model, downscaling processing of GPM data for three typical climate years can provide higher spatial resolution precipitation data for the Yellow River Basin region. The research results can, to some extent, provide reference and guidance for downscaling processing of satellite precipitation products in some regions of China under the same precipitation conditions and have important application value for hydro-meteorological research in areas with diverse climate conditions and complex terrain. However, this study still has some issues that require further research. First, the small number and uneven distribution of stations in the study area make it difficult to conduct more detailed accuracy verification, which reduces the accuracy of results. Second, the study area has complex landforms, and exploring more other environmental variables sensitive

to precipitation changes could establish a more reliable and stable model.

## 6. Conclusions

This study analyzed the downscaling effect of the MGWR model on GPM satellite precipitation products in the Yellow River Basin under different dry and wet climate conditions. The main conclusions are as follows:

- 1) In terms of original satellite precipitation product data, GPM annual precipitation data in the Yellow River Basin have good correlation with ground meteorological station observations. GPM data have good accuracy at the annual and station scales and demonstrate certain applicability within the study area.
- 2) The MGWR model significantly improved the spatial resolution of precipitation data in the Yellow River Basin compared with the original data. It can more accurately reflect the spatial distribution characteristics of precipitation in the study area. The MGWR model has stronger spatial detail expression capability than the GWR model, which is more significant in the wet year (2020) with abundant precipitation. The MGWR model's distinction between global and local variables can enhance the spatial expression capability of downscaled data.
- 3) In the three typical climate years in the Yellow River Basin, the downscaling results performed better in the precipitation standard year (2012). The accuracy of both GWR and MGWR data depends to some extent on the original data. The correlation between the downscaled data and meteorological station observation data did not improve and even lost some correlation, possibly because the complex natural geographical conditions of the study area, the selected environmental variables, and the downscaling models cannot fully explain the spatial heterogeneity of precipitation. At the same time, while improving resolution, some data accuracy was sacrificed [26].

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*Note: Figure translations are in progress. See original paper for figures.*

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